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ON THE CORRELATION OF GROUND MOTION INDICES TO DAMAGE OF STRUCTURE MODELS

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SUMMARY

Dynamic analysis of structure models is one of the most appropriate ways to estimate the response of a structure to a given time history of ground motion. When analyzing stochastic hazard models, however, the time history of ground motion is largely unknown. It is then more practical to work with ground motion indices such as peak ground acceleration (PGA) and acceleration response spectra (Sa) to represent ground motion from future events. A common set of ground motion indices is presented in the California Integrated Seismic Network (CISN) ShakeMap (i.e., PGA, PGV, Sa(0.3), Sa(1.0) and Sa(3.0)).

Recorded ground motion time histories were used to assess expected losses of structures based on seismic performance of structure models. The approach is based on the procedures developed by the Pacific Earthquake Engineering Research Center (PEER). The number of ground motion records is augmented by scaling the ground motion records.

This study calculates the ground motion indices for these time histories and correlates them with the damage ratios obtained from the detailed analyses. Neural networks, which have been successfully used to relate two or more ground motion indices to damage from simulated ground motions [1], are applied to process the large number of parameters and observations in the data set. The results of the analysis show how a combination of ground motion indices can be used to optimize the damage prediction for each structure type. Two standard steel moment-resisting frame structure models are used in this investigation.

After training, a neural network can accept ground motion indices provided by a ShakeMap and quickly estimate the mean damage ratio of a specific structure type. The information provided by ShakeMaps is then converted into damage ratio maps for a particular structure model. This capability extends the usefulness of the ShakeMaps by providing structure type specific damage distribution maps right after an earthquake.

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INTRODUCTION

Rapid damage estimation after a major event is critical in many aspects. For example, damage estimates can guide the response of emergency services and become the primary criterion for shutting down critical facilities like power plants or high-speed rail service. Dynamic analysis of structure models is still one of the best methods to predict the severity of the damage due to strong earthquake shaking. However, there are circumstances where a direct dynamic analysis is neither practical nor possible. If the time history of the ground motion is unknown, as in the case of future events, then it would be impossible to perform direct dynamic analysis. It becomes necessary to first model the expected ground motion for a given event.

In probabilistic seismic hazard analysis, the severity of the ground motion is still largely defined by attenuation relationships for a given ground motion index, such as peak ground acceleration (PGA), peak ground velocity (PGV), or acceleration response spectra (Sa). By using ground motion indices as the hazard value, it is implicitly assumed that a particular ground motion index is correlated with the damage of a particular building or facility. This paper looks into the relationship between common ground motion indices and building damage as determined from dynamic structural analyses.

DATA SUMMARY

The data used in this paper are composed of two parts: the first is the generation of a large set of strong ground motion time histories and the second is the dynamic analyses of two structure models based on realistic building configurations. Details on the methodologies used in developing the ground motion time histories and dynamic analyses are given by Rahnama, et al. [2]. A brief description is given in this paper to establish a background on the data being analyzed.

Strong ground motion records

There has been a fairly large amount of strong ground motion records from strong earthquakes in the United States, particularly in California. However, some analyses need such a large number of ground motion records that it is still necessary to augment the recorded strong ground motion time histories with simulated events.

Strong ground motion records from California earthquakes available from the Pacific Earthquake Engineering Research Center (PEER) are used as the basic data set. Table 1 shows the earthquakes and the number of time history records used. Each recorded ground motion time history is scaled to match a target response spectral value at a specific structural period. The target spectral values used range from 0.05g to 2.5g. The structural period of the target is matched to the fundamental period of the structure model to be analyzed with the scaled ground motion time histories.

Common ground motion indices are determined for each of the scaled ground motions. These are PGA, PGV, and acceleration response spectra amplitudes for periods equal to 0.3, 1.0, and 3.0 seconds. These three periods are chosen to match the response spectra periods reported by ShakeMaps. The PGA is directly available from the acceleration time histories while the PGV is calculated by integrating the acceleration time history in the frequency domain. The response spectra values correspond to the 5% damped elastic response spectrum for each ground motion time history.

Table 1. Events and number of ground motion records used in this study.

Date	Event Name	Magnitude	# of records used
1983	Coalinga	6.5	90
1984	Morgan Hill	6.2	46
1987	Whittier-Narrows	6.0	104
1989	Loma Prieta	7.0	72
1992	Big Bear	6.4	48
1992	Landers	7.3	34
1994	Northridge	6.7	86
	Total Number of records		480

Dynamic analysis

The scaled strong ground motion records developed are then applied to two standard structure models representing 3- and 9-story steel frame structures. The two structure models analyzed are SAC Steel Project models defined by Gupta and Krawinkler [3] and shown in Figure 1. The strong ground motion records are applied to the structure model and analyzed using the DRAIN-2DX software. The software package gives the maximum inter-story drift for each story. The inter-story drifts are translated into damage ratios per story and the mean damage ratio (MDR) for the structure is calculated as the average of the damage ratios per story.

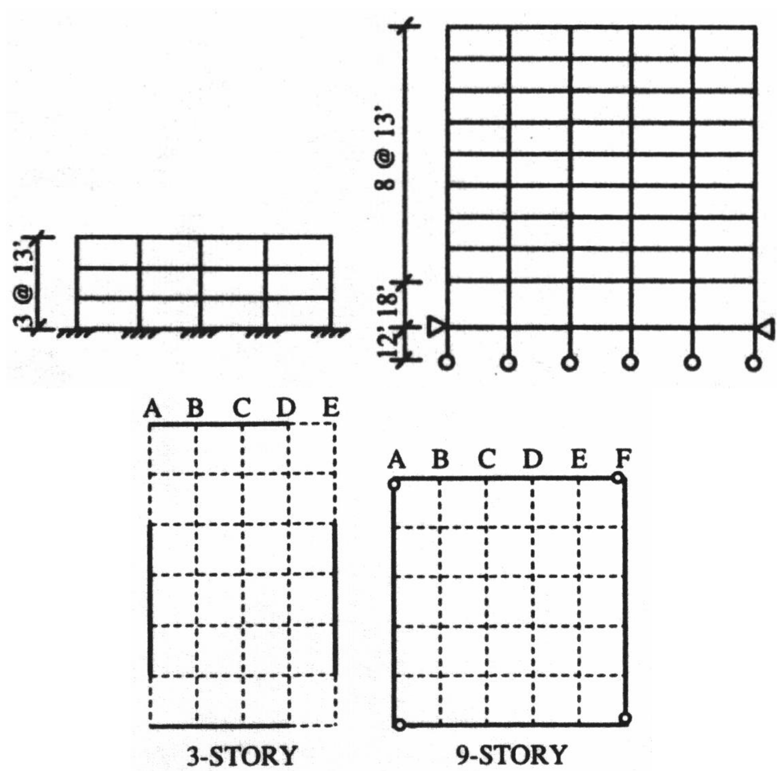

Figure 1. Schematic figure of steel frame structure models used in this study (Gupta and Krawinkler [3])

RELATIONSHIP OF GROUND MOTION INDICES AND MEAN DAMAGE

The relationship between ground motion indices and structural damage becomes very difficult to define when the response of the structure becomes nonlinear. Basic ground motion indices such as PGA or PGV give a single dimension of the ground motion characteristics, while the degree of structural damage often depends on several factors, including the characteristics of each particular structure.

Figure 2 shows the distribution of the mean damage ratios estimated for the 3-story steel structure model due to the scaled ground motion time histories, with respect to the corresponding ground motion indices. At the lower range of the ground motion index values, there is a defined correlation between the ground motion indices and the mean damage ratio. However, as the intensity of the ground motion increases and the structural response transitions into nonlinear behavior, the correlation quickly becomes less apparent. In the case of the PGA, this implies that the mean damage ratio for the 3-story structure becomes less dependent on the PGA as the ground motion intensity increases. The plot of the mean damage ratio with respect to the PGV is more defined than that for the PGA. Although the scatter is still wide, it is apparent that the PGV has a better correlation with the mean damage ratio than the PGA. The correlation of the mean damage ratios with respect to the acceleration spectra for 0.3 and 1.0 seconds fall somewhere in between. Although not shown here, the distribution of the mean damage ratio with respect to the acceleration response for a 3 second period shows very low correlation.

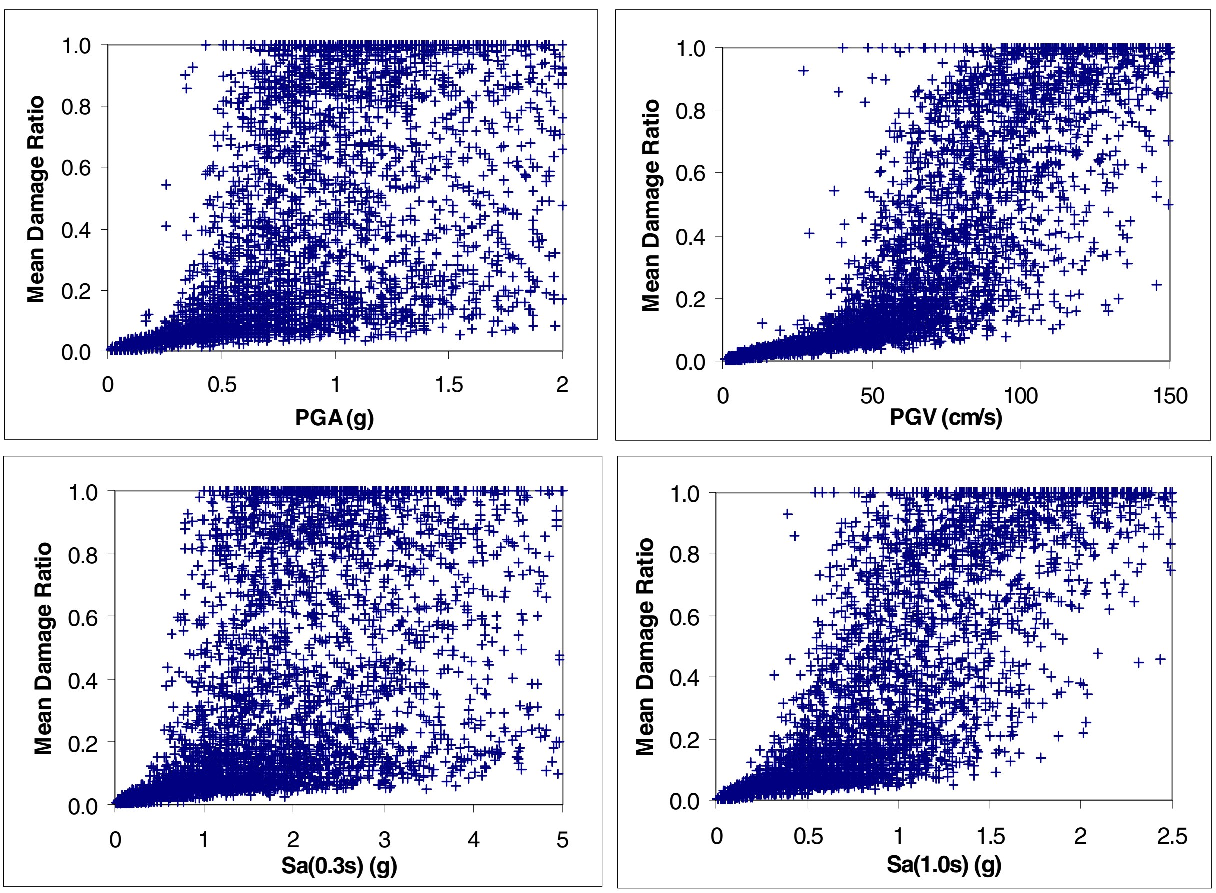

Figure 2. Distribution of calculated mean damage ratio of 3-story steel frame building model with respect to selected ground motion indices

Another way to look at how well an independent variable predicts a dependent variable is to look at the dispersion of the dependent variable (MDR) for a given value of the independent variable (ground motion index). The coefficient of variation or CV (ratio of the standard deviation to the mean) of the mean damage ratio is calculated to quantify this dispersion. Figure 3 shows the plot of the mean and CV with respect to some of the ground motion indices. A lower CV signifies a lower variation of the mean damage ratio with respect to a particular value of the ground motion. The plot of the CVs shows that at lower levels of ground shaking, the ground motion indices has relatively constant CV, indicating that the ability of the ground motion index to predict the mean damage ratio is fairly constant.

However, as the level of ground shaking increases, there is a sudden increase in the calculated CVs. This behavior is probably caused by the transition of the structural response from linear to nonlinear. For all the ground motion indices in Figure 3, the jump in the CV is more than twice the "weak-motion" CVs. After the peak, there is a continuous drop in the CV as the ground shaking intensifies. However, this apparent improvement in the ability of the ground motion index to predict the MDR is simply a side effect of the saturation of the MDR at 1.0. Since the MDR is capped at 1.0, as the ground motion gets stronger, more and more records are causing the structure models to achieve an MDR of 1.0.

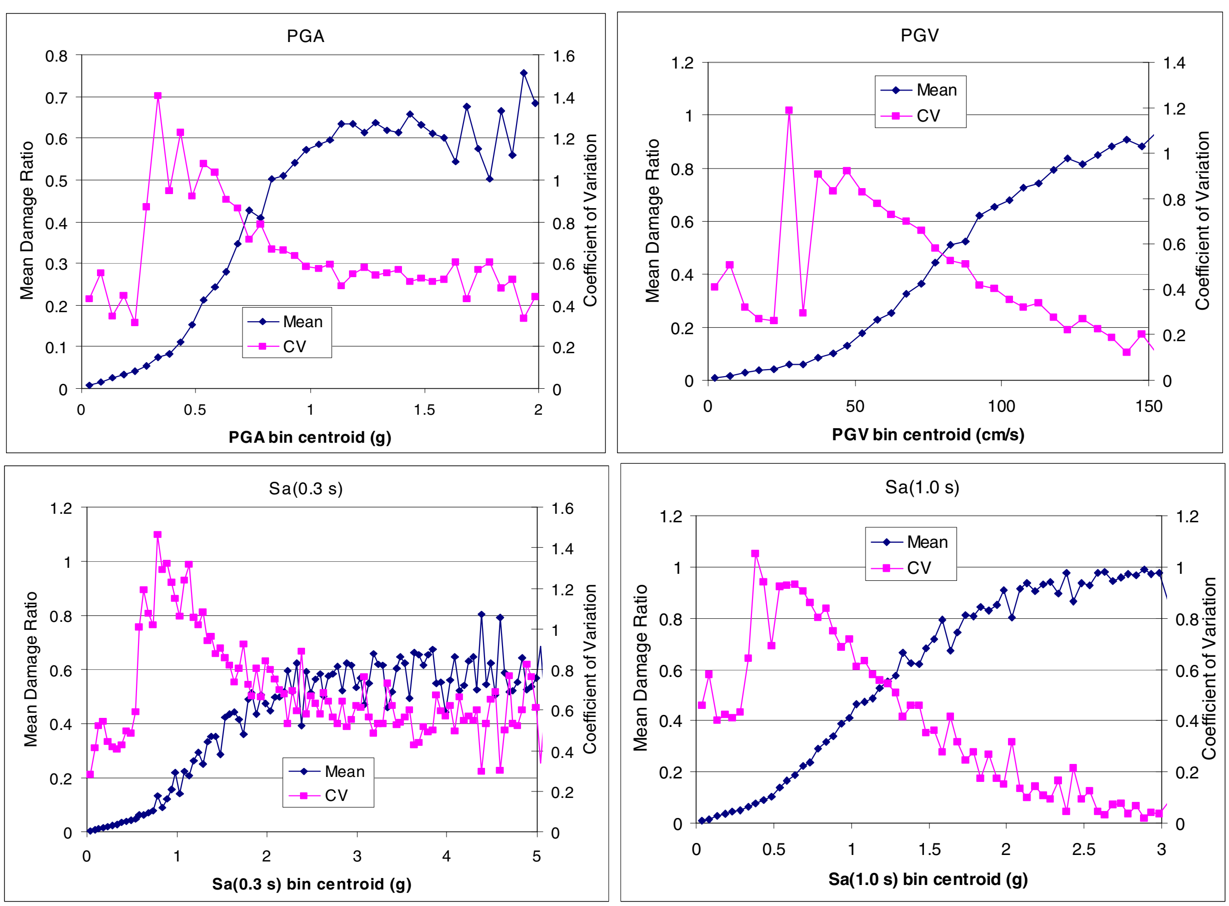

Figure 3. Mean and coefficient of variation (CV) of the mean damage ratio per bin of the ground motion indices for the 3-story steel structure [clockwise from top left: PGA, PGV, Sa(1.0s), Sa(0.3s)]

METHODOLOGY

This study investigates the feasibility of using a neural network model to correlate multiple ground motion indices with the mean damage ratio of a specific structure model. A neural network model has been shown to effectively predict the ductility factor of single-degree-of-freedom models using ground motion indices [1]. The current study uses more complicated structure models and ground motion indices based on recorded actual acceleration time histories. With more complicated mechanisms for nonlinear behavior occurring in a more realistic structure model, it is interesting to see how well the neural network model can predict the mean damage ratio from basic ground motion indices.

A neural network is a "free-form" model that does not require *a priori* knowledge of the relationship between the dependent (output) and the independent (input) variables. It is also very good at capturing nonlinear relationships. However, like the human mind, neural networks would have to be presented with numerous examples of "true" instances of the input and output variables. The examples are repeatedly fed into the network while it adjusts its internal connection weights to minimize the difference between the target output and the calculated output. This process is called training the neural network. There are several algorithms available to train neural networks. This study uses a variation of error back-propagation technique called the extended delta-bar-delta rule (EDBD) developed by Minai and Williams [4]. Details of the training data and neural network configuration are discussed in the next sections.

Training Data

The input variables used by the neural network are the ground motion indices determined from the scaled ground motion time histories. Only one output variable, the mean damage ratio, is used in the neural network model. Note that since the mean damage ratio is dependent on the structure model analyzed, the training data is unique to a particular structure model.

There are a couple of steps taken to improve the efficiency of the training process. The first step is the selection of the training data to have a balanced distribution within the ranges of the input and output variables. Figure 4 shows the number of data for ranges of PGAs and PGVs in the training set. The large number of data in the lower ranges of the ground motion indices might result in a bias of the training process. To mitigate this effect, the training data are divided into 50 groups based on the mean damage ratios. For each group, data are randomly selected so that the number of data per group does not exceed 50. This reduced the number of training data for the 3-story structure model from 5,293 to 2,115. A lot of information may have been lost by the random selection of the training data, but it is hoped that the neural network would be able to generalize the behavior of the mean damage ratio at the low ranges of ground motion indices from the reduced set of training data.

The second step is the scaling of the input and output variables to a specific range. One important effect of scaling is that it removes the effect of units in the input and output variables. If one variable has relatively large values compared to the other variables, this variable will saturate the network and the network might take several training cycles before it could recover. The variables are scaled by the following equation:

$$\tilde{x} = l_L + (l_H - l_L)\left(\frac{x - x_{\min}}{x_{\max} - x}\right) \tag{1}$$

where $\tilde{x}$ is the scaled value of x, l_L and l_H are the desired lower and upper limits of the scaled value, respectively, and $x_{\min}$ and $x_{\max}$ are the minimum and maximum values, respectively, of parameter x in the training data set. The l_L and l_H of input values are –1.0 and 1.0, respectively. For output values, l_L is –0.8 and l_H is 0.8. The output limits are based on the hyperbolic tangent transfer function used in the neural network.

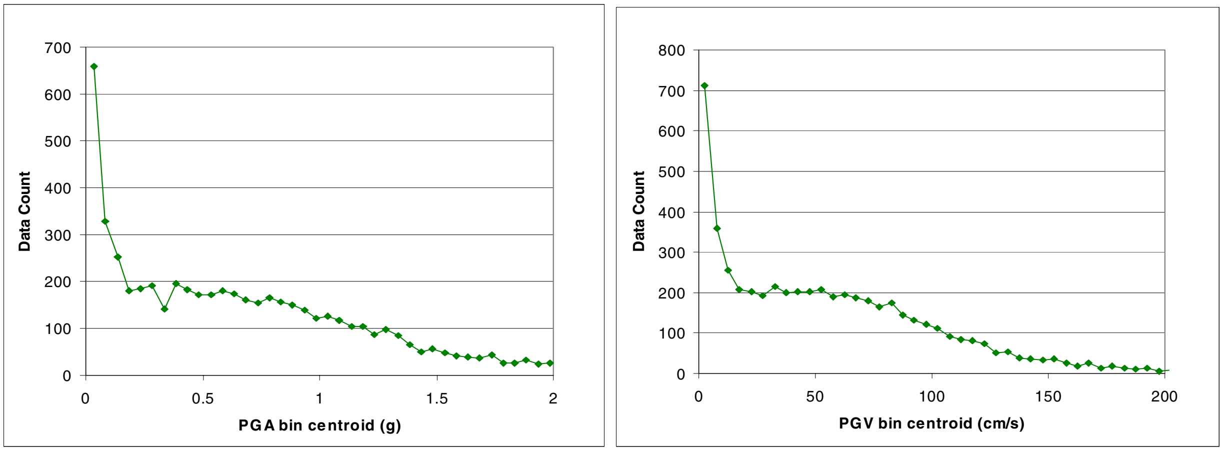

Figure 4. Number of training data for each narrow range of PGA and PGV values.

Table 2. Minimum and maximum values used in the scaling

Input Variable	x_{min}	x_{max}
PGA (g)	0.01	1.99
PGV (cm/s)	1.56	256.32
Sa (0.3 s)	0.02	8.59
Sa (1.0 s)	0.01	4.04
Sa (3.0 s)	0.001	1.20
MDR	0.00	1.00

Neural Network Model

A neural network is a collection of parallel processors connected in a form of a directed graph. It consists of neurons or Processing Elements (PEs) that are arranged in layers. The neural network used in this study is a three-layered feed-forward neural network with full connectivity and bias (Figure 5). The bottom layer, called the input layer, holds the input vector and has one PE for each input variable in the input vector plus an optional bias PE. The top layer, called the output layer, holds the output values of the network. Between the input and output layers, there can be one or more hidden layers with any number of PEs. For this study, one hidden layer with 8 PEs and bias is used. However, different configurations of the neural network may work just as well.

Input data are fed to the input layer and the processing is done layer-by-layer up to the output layer. The output values of the hidden layer and output layer PEs can be expressed as

$$out_j^h = f^h\left(\sum_{i=1}^{N} \omega_{ji}^h \cdot x_i + \theta_j^h\right) \quad \text{and} \quad out_k^o = f^o\left(\sum_{j=1}^{M} \omega_{kj}^o \cdot out_j^h + \theta_k^o\right) \tag{2}$$

respectively, where ω_{ji} is the connection weight of the j^{th} PE from the i^{th} PE of the input layer, x_i, is the i^{th} scaled input, θ_j, is the bias term for the j^{th} PE and f is the transfer function between the two layers. The superscripts define the variables for the outer layer and the hidden layer. The transfer function used in this study is the hyperbolic tangent transfer function.

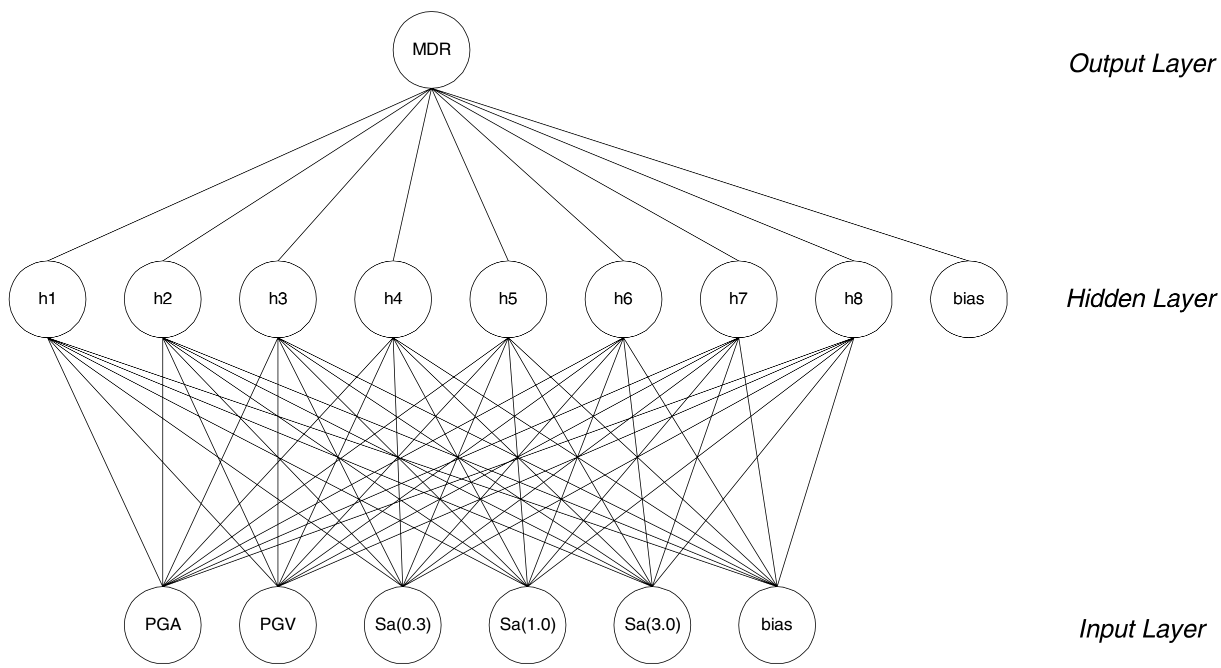

Figure 5. Neural network structure used in this study

RESULTS

The training of the neural network is an iterative process to minimize the "error" in the neural network prediction with respect to the training data output. We quantify the error in terms of the root-mean-square (RMS) error defined as:

$$E_{RMS} = \sqrt{\frac{1}{N}\left(\sum_{N=1}^{n}\left(des_n - out_n\right)^2\right)} \qquad (3)$$

where des_n is the mean damage ratio associated with the n^{th} input vector, out_n is the output of the network, and N is the total number of input vectors in the training set. After a large number of iterations, the RMS stabilizes and the network can then be considered as fully trained and ready for testing. Table 3 gives the error statistics for the trained neural network and Figure 6 shows the distribution of the predicted vs. target mean damage ratios for the two structure models analyzed here. The neural network was able to obtain a good correlation between the predicted and target mean damage ratios, but there is still a wide range of scatter along the 1:1 line. There is also an apparent bias in the network output at the lower ranges compared to the results of dynamic analyses. Normally, neural networks can easily handle nonlinear behavior such as the ones seen in Figure 6. However, for the back-propagation neural network used in this study, the optimization is based on the overall system error and may not care for the bias if there is no benefit (decrease in the total error) from the training data. It is noted that the over prediction in the lower ranges are balanced by some under prediction in the higher ranges. More studies are needed to fully understand this behavior and how to eliminate it. One possibility is to perform a transformation of the output variable and/or to reconfigure the training data set.

It should also be noted that the choice of the ground motion indices used in this study is based on the ShakeMap. It is possible that the acceleration response spectra for periods that are more tuned to the structure model will give better correlation with the target mean damage ratios.

Table 3. Error statistics for the training data after the end of training

Statistic	3-story structure	9-story structure
RMS error	0.17908	0.13386
Correlation	0.82056	0.82713

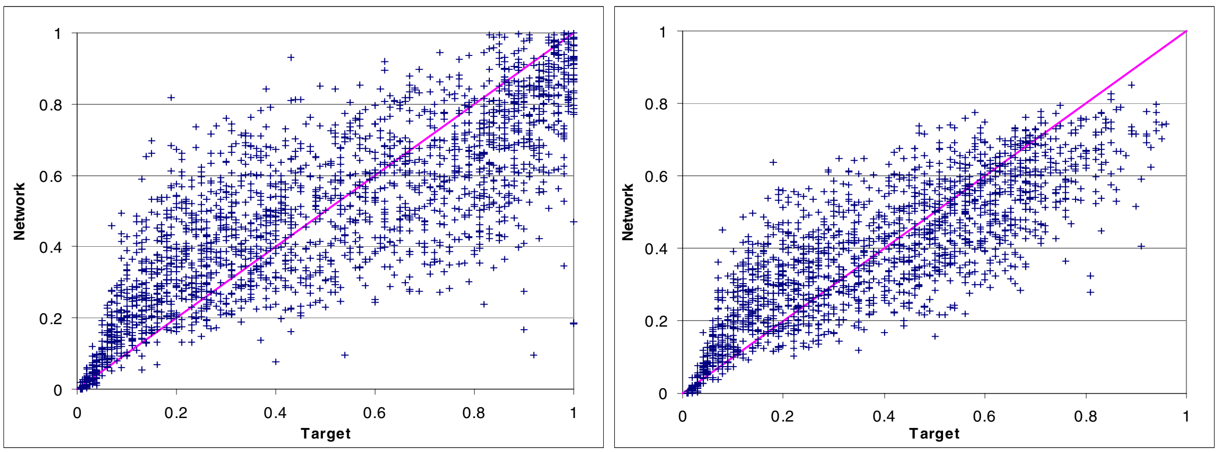

Figure 6. Comparison of the target mean damage ratios with the network predicted mean damage ratios for the 3-story steel structure model (left) and the 9-story steel structure model (right.) This figure shows the data points for the training data only.

Sensitivity Analysis

Neural networks function like the proverbial black box, where it is very difficult to understand how the network is working. While it is easy to calculate the network output once the connection weights are determined, it is not always easy to determine which input parameter has a greater influence in the determination of the network prediction. However, it is possible to get a qualitative view of the sensitivity of the neural network prediction to the input variables by calculating the partial derivatives of the output PE with respect to an input variable [1]. It has been shown that the partial derivative of the output PE is dependent not only on the weights and biases of the network, but also on the current values of all the input variables.

Figure 7 shows the histograms of the partial derivatives of the scaled output with respect to each of the scaled inputs in the training data for the 3-story structure model. A partial derivative close to zero signifies that a change in the input variable will not have a significant effect on the output variable if all other input variables are held constant. A data point in the histogram shows the number of times that the partial derivative is equal to that value. Therefore, if a histogram shows a large number of data close to zero, then the output is relatively insensitive to the particular input variable. The plot of the partial derivatives with respect to PGA shows a wide dispersion but with the peak close to zero. The histogram of partial derivatives with respect to the PGV gives a peak closer to 1.0. From these observations, it can be concluded that the neural network output is sensitive to the PGA, PGV, and Sa(1.0) and is relatively insensitive to the response spectra values at 0.3 and 3.0 seconds. This may be related to the fact that the period of the structure is about 0.6 seconds. It should be noted that if a different set of input variables is used, the histograms of the partial derivatives might give different characteristics. For example, if two variables used in the input layer are correlated, then the neural network might use only one of them for the output calculation. If this input variable is removed, then the other correlated variable will become more active in the calculation of the network output.

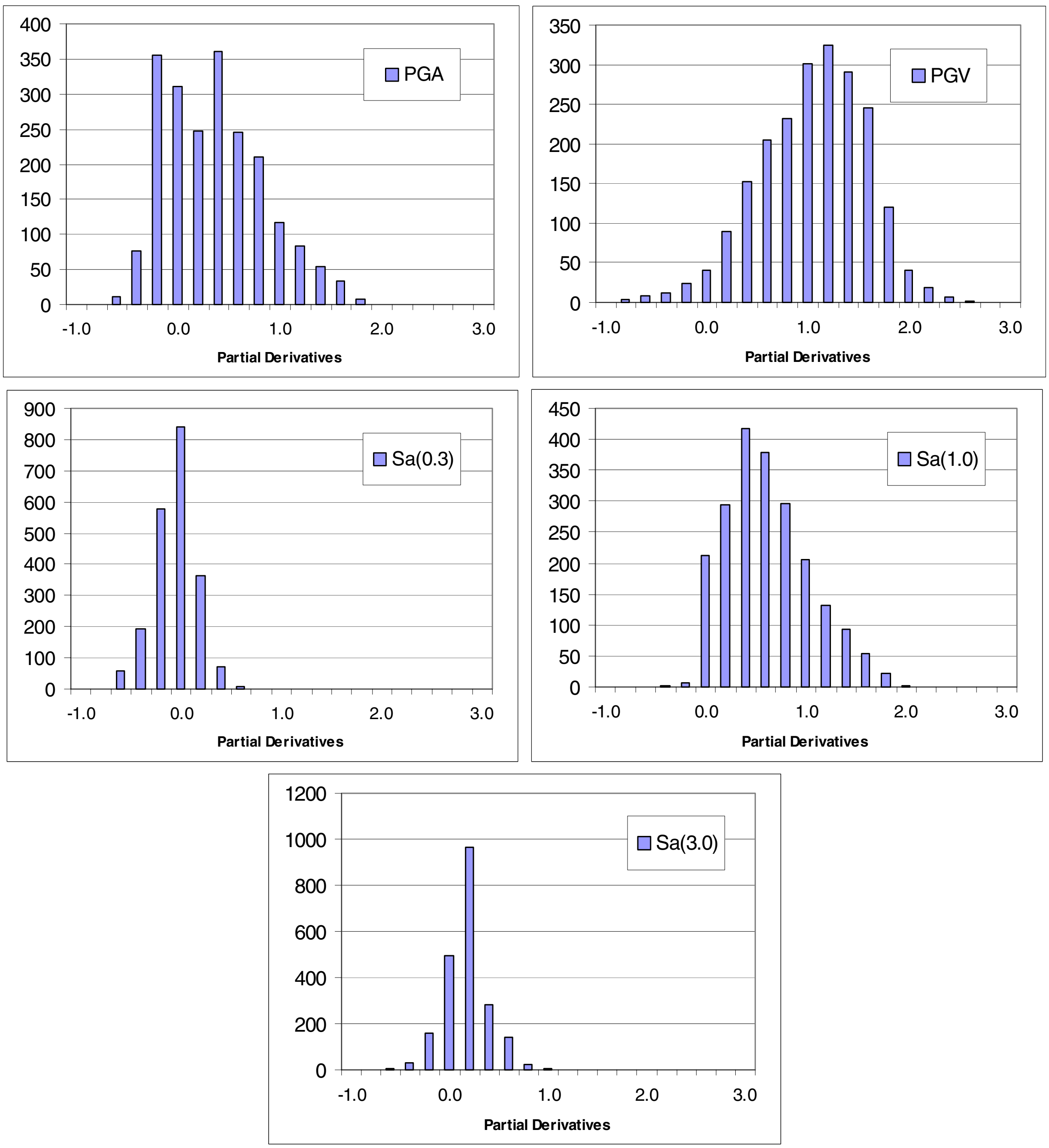

Figure 7. Histograms of the partial derivatives of the scaled output with respect to the scaled inputs for the 3-story structure model. The model has a fundamental period of 0.6 sec.

To test the efficiency of the neural network model in predicting the mean damage ratios, the combination of input variables were modified. For each case, the network was re-trained until the RMS error converges. Table 4 shows the combination of input variables analyzed and the resulting error statistics for both structure models. It can be seen that using the full set of input variables gives a better correlation with the mean damage ratios for both steel structure models.

Table 4. Error statistics for the different combinations of input variables for the two structure models

	3-story structure		9-story structure	
Input Variables	RMS error	Correlation	RMS error	Correlation
PGA, PGV, Sa(0.3), Sa(1.0), Sa(3.0)	0.1791	0.8206	0.1339	0.8271
Sa(0.3), Sa(1.0), and Sa(3.0)	0.2011	0.7670	0.1433	0.7988
PGA and PGV	0.1924	0.7893	0.1549	0.7598
PGA and Sa(1.0)	0.2004	0.7689	0.1704	0.6990
Sa(0.3) and Sa(1.0)	0.2067	0.7519	0.1712	0.6958

APPLICATION TO SHAKEMAPS

ShakeMaps

After the occurrence of a significant earthquake in California and some other parts of the U.S., the California Integrated Seismic Network (CISN) publishes ShakeMaps, which use ground motion recorded by a network of sensors to create a footprint of selected ground motion indices. These maps are very useful in assessing the extent of the actual ground shaking and the distribution of possible damage, even before any field reconnaissance of the affected area.

Since individual ground motion indices become uncorrelated with the damage as the level of ground shaking increases, this study attempts to efficiently generate a map of damage estimates using the values provided by the ShakeMaps. As mentioned previously, the selection of the input variables in this study is intentionally matched to the ShakeMap variables. With the grid data file that can be downloaded from websites of member organizations of the CISN (e.g., the USGS), the text file can be processed and quickly converted to mean damage ratio estimates for each of the grid points defined by the ShakeMap. Figure 8 shows the mean damage estimates for the 3-story steel frame structure analyzed in this study for the ground motion indices of the 1994 Northridge earthquake provided by the ShakeMap. If several, structure models are trained beforehand, then a suite of damage ratio distribution maps can be immediately generated as soon as the ShakeMaps are published. For example, structure models that represent public buildings (e.g., schools, hospitals, and emergency services) might be analyzed so that damage estimates can be quickly generated.

CONCLUDING REMARKS

This paper looks into the correlation between ground motion indices and mean damage ratio estimates for specific structure models. Although ground motion indices correlate well when the level of ground shaking is low, the correlation quickly breaks down as the structure transitions into nonlinear behavior.

A neural network model is used to correlate the mean damage ratios with the ground motion indices at the higher levels of ground shaking. Multiple ground motion indices are used simultaneously to come up with an estimate of the mean damage ratio. This paper uses the ground motion indices provided by ShakeMaps to effectively extend its usefulness by adding the ability to generate damage distribution maps for particular structures. Additional studies are needed to test if the estimation of the damage ratios can be improved by a different selection of neural network configuration and/or training data selection.

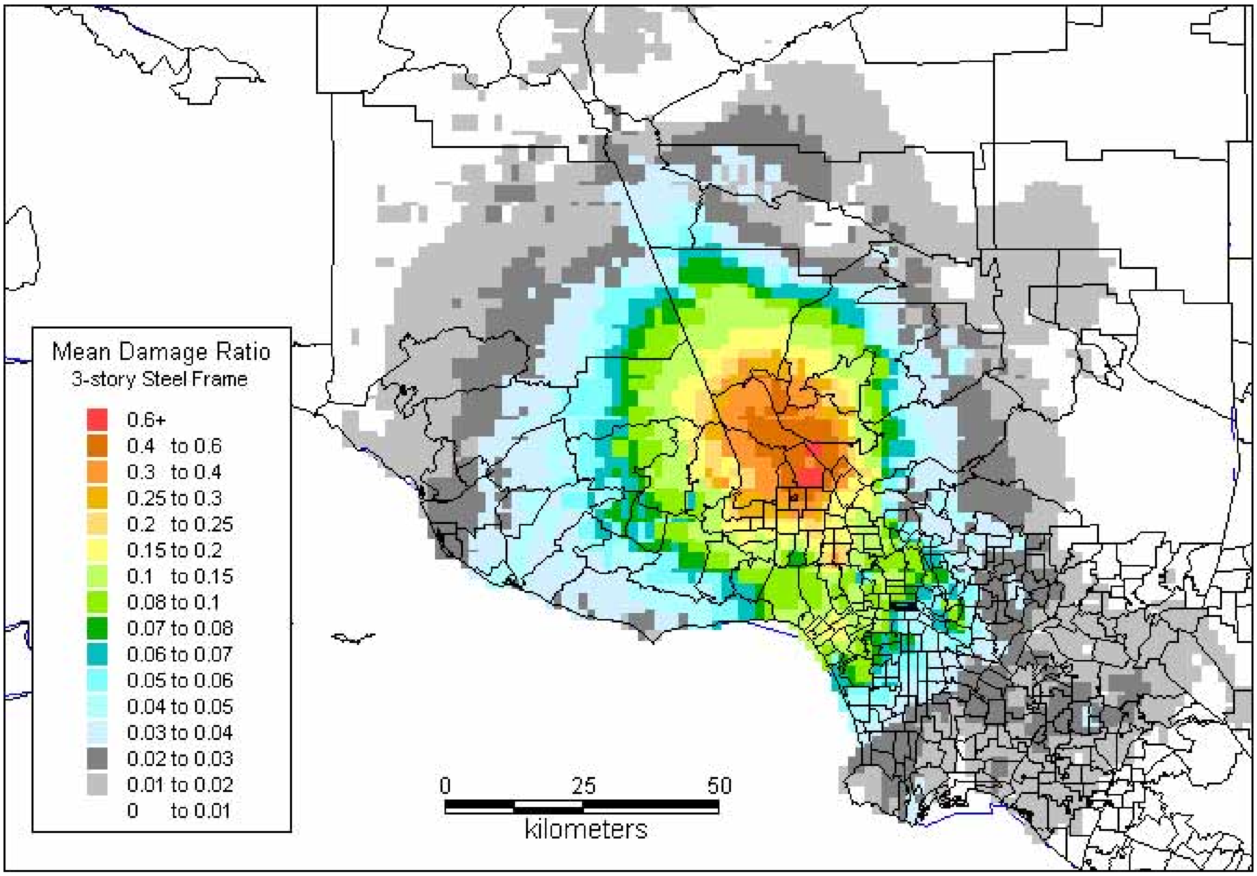

Figure 8. Neural network prediction of MDRs for 3-story structure due to the Northridge earthquake

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